Chapter Three RESEARCH DESIGN

3. Research Design

The purpose of this research was to generalize findings about consumer attitudes towards AMCs of multibrand fashion from a sample of a population to the population itself, in order to derive inferences about fashion repurchase intentions of the target population (Creswell, 2014). The research onion (Figure 2.) adapted from Saunders *et al.* (2019) illustrates the various stages included in the design of this study.

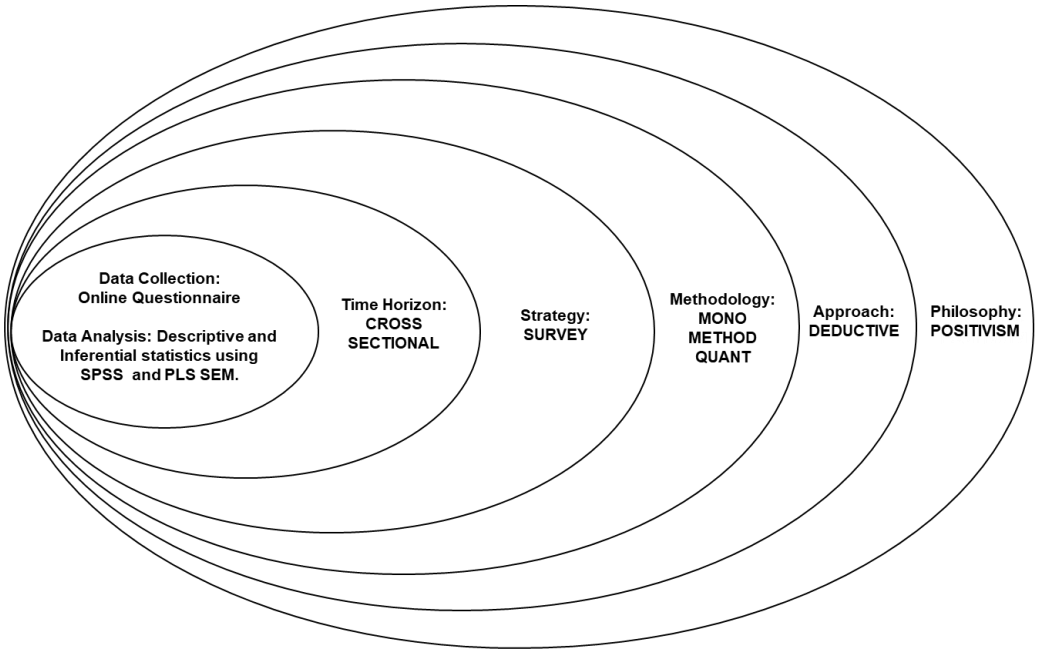

Figure 2: The Research Onion as adapted from Saunders *et al. (2019).*

3.1. Philosophical Context

Previous studies on the subject of app marketing followed highly structured and replicable methodologies, demonstrating the use of an underlying positivist philosophy (McLean *et al.*, 2019; Antwi, 2021; Lim *et al.*, 2021; Tseng, Hsieh and Lee, 2021). From a philosophical perspective this research too, was designed on the foundations of positivism. Epistemologically, positivism constitutes 'working with observable social reality' in order to test hypotheses and derive 'law like generalizations' similar to those produced by scientific research (Saunders *et al.*, 2019). Ontologically, adopting a positivist stance for this research facilitated an 'objective' study of reality. This is was advantageous since by placing the researcher external to the process of data collection, the study could generate 'value-free' findings (Saunders *et al.*, 2019).

Although a positivist approach may lack the depth of research achievable by exploratory studies, extant literature around app marketing has already theorized several models in the domain of app marketing (McLean *et al.*, 2019; Antwi, 2021; Lim *et al.*, 2021; Tseng, Hsieh and Lee, 2021). Thus, in contrast to interpretivism, adopting a positivist stance was more suitable since this study attempted to build on such existing frameworks by validating them in other contexts and geographies, as opposed to devising new theories (Saunders *et al.*, 2019). Moreover, limitations articulated in previous exploratory studies on agile marketing highlighted the need to examine AMCs from a consumer perspective using empirical evidence (Hagen, Zucchella and Ghauri, 2019; Moi and Cabiddu, 2020). Adopting a positivist stance for this study therefore provided a foundation to gather such empirical evidence in the form data collected to study consumer behaviour on multibrand fashion apps in the U.A.E.

3.2. Research Approach and Design

This research was designed deductively using a mono-method quantitative methodology. As the research objectives were explanatory (i.e., seeking to explain causal relationships between fashion app marketing and consumer behaviour) a deductive approach was selected (Saunders *et al.*, 2019). This is because unlike exploratory studies on retail apps such as that by Parker and Wang (2016), this research did not intend to build new theories but instead focused on verification or falsification of existing literature. Adopting a deductive approach facilitated the reductionist aspect of positivism, in the sense that the reviewed literature was deductively reduced into discrete variables and hypotheses (Creswell, 2014).

This approach also enabled the replication of methodologies followed in previous studies whilst also attempting to enhance the replicability of this research for future academics (Bryman and Bell, 2011). In line with replicability, a survey strategy was adopted for the data collection process as observed in previous studies (Kim et al., 2016; McLean et al., 2019; De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021). This strategy offered several advantages including economic feasibility and rapid turnaround (Creswell, 2014). Moreover, a survey also provided the ability to accurately make inferences about the population's characteristics limited to an accepted degree of error (Clow and James, 2014).

Although an experimental approach may have provided greater confidence in establishing *causality* between variables as observed in the study by Watson, Alexander and Salavati (2020), a survey-based approach still allowed the *inference of correlations* between variables

in an economical manner (Bryman and Bell, 2011). Inferring correlations further enabled the validation of formulated hypotheses (Bryman and Bell, 2011). Also, unlike an experiment, this study took place in an uncontrolled environment without involving treatment/ intervention of the independent variables, and was therefore suitable for a survey (Creswell, 2014).

3.3. Instrument Design

3.3.1. Design and Layout

The survey was conducted using an online questionnaire. The questionnaire was created on Qualtrics using pre-existing scales to increase reliability and validity (Bryman and Bell, 2011). However, to suit the context of this study some scales were adapted, and a few original items were also developed. This was similar to the approach taken by other researchers who also used pre-tested scales (Creswell, 2014; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021).

In line with the guidelines prescribed by Brace (2008), the questionnaire was structured in blocks as illustrated in Table 5. below. (Please see Table 6. for the code book used for this study and Appendix 3 - A 3.5. for the complete questionnaire).

According to Brace (2008), including more than 30 statements in the questionnaire may induce respondent fatigue. However, since this survey required the measurement of nine variables, behavioral data, and demographics, the questionnaire had a total of 38 statements. This was still less than some of the other questionnaires reviewed in literature which had around 46 – 68 statements (McLean *et al.*, 2019; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021). While some other studies such as those of Antwi (2021) and Ali and Bhasin (2019) had about 30 questions, it is worth noting that these questionnaires did not seem to collect any behavioural data. Moreover, Antwi's (2021) sequence of collecting participant's background information before construct-related data may have induced respondent fatigue which wasn't accounted for.

Table 5: Block structure of the questionnaire designed.
Please see Appendix 3 – A 3.5 for the complete questionnaire.

Block		Design and Content
1.	**Cover Page**	The research was introduced as a general consumer behaviour study on local multibrand fashion apps. **Any intimation about agile marketing capabilities in particular was avoided to minimize respondents predictability about any causal links between the constructs** (Clow and James, 2014). The jargon of 'Pureplay Multibrand Fashion App' was clarified with a simple definition and appropriate examples. A logo of UAL was also included to increase the authenticity of the research and make it worthy of the respondent's time. The cover page also outlined guidelines relating to voluntary participation, duration of survey, data protection and privacy disclosure, and consent.
2.	**Screening Questions**	Two dichotomous (yes or no) screening questions regarding location and previous shopping experience with multibrand fashion apps were developed to funnel only those respondents who were based in the U.A.E and had purchased something at least once in the past two years from such apps. The two year time limit was proposed to account for any potential shopping breaks during the COVID 19 pandemic.
3.	**Behavioural Questions**	Respondents were made to reflect on their app usage behaviour in order to position themselves for the upcoming attitudinal questions. This block included four nominal questions relating to most **commonly used app, purpose of use, frequency, and usage location**. **Allowing respondents to recall their behaviour before attitude would avoid eliciting spontaneous responses for the main constructs** (Brace, 2008). In addition, since one of the aims of this study was to develop managerial recommendations, asking behavioural questions provided rich insights to develop these recommendations.
4.	**Constructs (Attitudinal Questions)**	Respondents were asked to indicate the level of disagreement/ agreement with various AMCs (i.e., independent variables), internal states (PAD), and repurchase intentions using five-point Likert scale items. Arousal and Pleasure were measured using five-point semantic differential scales. **Although seven-point Likert scales provide greater precision, five-point scales were used to make the questionnaire more user-friendly**. Each construct was measured with a **minimum of three items, in case of having to delete a scale on grounds of poor reliability and validity** (Hair *et al.*, 2010)**.**
5.	**Demographic Questions**	**Gender, age, and occupation** related questions were asked at the end in order utilize greater attention span of the respondent for the behavioural and attitudinal questions at the beginning.
6.	**Lucky draw opt-in**	Respondents interested in participating in the lucky draw could chose to input their contact details.
7.	**Note of Thanks**	A short message conveying the researcher's gratitude and signaling that all responses had been recorded was displayed the end of the survey.

3.3.2. Mitigating Bias

Owing to the length of this questionnaire, various procedural and statistical remedies were adopted to minimize instrument and respondent bias. To control for acquiescence (tendency to agree) the Likert scale options were displayed from negative to positive. This would result in the 'least favorable response pattern', and hence a 'tougher test' for the hypotheses (Brace, 2008). To minimize primacy effect (tendency to recall first option), the options for nominal questions were randomized (Brace, 2008). Although McLean's (2019) study randomized the scales of constructs as well (to reduce Common Method Bias (CMB)), the options and order of Likert scale constructs were not randomized for this study. Randomization of Likert scale questions was avoided to ease the reader into the flow of the survey (Brace, 2008). Pattern responding and inattention was accounted for by including an Instruction Manipulation Check (IMC) (Oppenheimer, Meyvis and Davidenko, 2009; Hsieh, Lee and Tseng, 2021). The IMC was designed as a standard Likert scale question to camouflage with the other statements. It prompted respondents to tick the 'neutral' option in order to filter out those who did not pay attention. The survey also attempted to minimize attrition by motivating users to reach the end of the questionnaire to enter into the lucky draw (Clow and James, 2014). In addition, respondents were also given an idea of the duration it would take to complete the survey.

Apart from the procedural remedies, statistical testing using Harman's one factor test was also performed in order to eliminate the likelihood of CMB arising from self-selection bias as discussed in the data analysis in section 4.2 (Podsakoff *et al.*, 2003; Hsu and Chen, 2018).

3.3.3. Code Book

Table 6. presents the code book used for data analysis. It illustrates the various measurement items, data types, sources, and coding instructions for data analysis using SPSS V.27 and Smart PLS 3. It is important to note that the code book does not contain any demographic or behavioural questions (such as purpose of app usage, location, frequency). These have been recorded in the complete questionnaire presented in Appendix 3 – A3.5.

Table 6: Code Book containing all the variables used for hypotheses testing. Behavioral, Demographic, and Screening questions have been omitted from the code book. Refer to Appendix 3 - A 3.5. for the complete questionnaire containing all the questions.

Constructs and Measurement Items		Source	Coding
AMCs – Antecedents. *Five-point Likert scale items*			
	Newness of Assortment	(Lim *et al.*, 2021)	1 (Strongly Disagree) to 5 (Strongly Agree). Mean: A number out of 5 (=(3 x 5) / 3)
NoA_1	*This app sells various trendy fashion assortments. Adapted*		
NoA_2	*This app offers fashion products with new designs. Original*		
NoA_3	*This app is up to date with new product launches. Adapted*		
NoA	*Total Score for Newness of Assortment*		
	Personalization	(Hsieh, Lee and Tseng, 2021)	1 (Strongly Disagree) to 5 (Strongly Agree). Mean: A number out of 5 (=(3 x 5) / 3)
PER_1	*I feel this app can be personalized for my usage. Adapted* ***(deleted post pilot)***		
PER_2			
PER_3	*There are personalized contents in this app. Adopted*		
PER_4	*This app personalizes product recommendations to suit my taste. Original*		
	This app displays personalized advertisements based on my usage. Original		
PER	*Total score for Personalization.*		
	Transparent User Experience	(Lim *et al.*, 2021)	1 (Strongly Disagree) to 5 (Strongly Agree). Mean: A number out of 5 (=(4 x 5) / 4)
TUX_1	*I know when my order has been shipped or is being compiled using this app. Adopted*		
TUX_2			
TUX_3	*The delivery information is readily available when using this app. Adopted*		
TUX_4	*I know when my order has been received using this app. Adopted*		
TUX	*This app has a transparent payment procedure. Original* Total Score for Transparent User Experience		
	Ubiquity	(Hsieh, Lee and Tseng, 2021)	1 (Strongly Disagree) to 5 (Strongly Agree). Mean: A number out of 5 (=(3 x 5) / 3)
UBQ_1	*I can use this app anytime. Adopted*		
UBQ_2	*I can use this app anywhere. Adopted*		
UBQ_3	*I expect the app would be available to use whenever I need it. Adopted*		
UBQ	Total Score for Ubiquity		
	After-Sales Services	(Lim *et al.*, 2021)	1 (Strongly Disagree) to 5 (Strongly Agree). Mean: A number out of 5 (=(3 x 5) / 3)
AFS_1	*The after-sales services provided by this app are fast Adapted*		
AFS_2	*The return/ exchange process using this app is fast. Original*		
AFS_3	*This app is quick to process any refund requests. Original*		
AFS	*Total Score for After-Sales Service.*		
Organism States – Mechanism. *Semantics Differential Scales and Five-point Likert scale items.*			
	Pleasure - *When I use this app, I feel:*	(Hsieh, Lee and Tseng, 2021)	1 (Strongly Disagree) to 5 (Strongly Agree). Mean: A number out of 5 (=(3 x 5) / 3)
PLE_1	*Unhappy – Happy Adopted*		
PLE_2	*Annoyed – Pleased Adopted*		
PLE_3	*Dissatisfied – Satisfied Adopted*		
PLE	*Total Score for Pleasure*		
	Arousal - *When I use this app, I feel:*	(Hsieh, Lee and Tseng, 2021)	1 (Strongly Disagree) to 5 (Strongly Agree). Mean: A number out of 5 (=(3 x 5) / 3)
ARO_1	*Sleepy – Active Original*		
ARO_2	*Calm – Excited Adopted*		
ARO_3	*Relaxed (laid-back) – Stimulated (energized) Adapted*		
ARO	*Total Score for Arousal*		
	Dominance	(Hsieh, Lee and Tseng, 2021)	1 (Strongly Disagree) to 5 (Strongly Agree). Mean: A number out of 5 (=(3 x 5) / 3)
DOM_1	*I feel like I have a lot of control over my usage experiences on this app. Adapted*		
DOM_2			
DOM_3	*When I am on this app, I can choose freely what I want to see. Adapted*		
	While using the app, my actions decide the kind of experiences I get on this app. Adapted		
DOM	*Total Score for Dominance*		
Repurchase Intentions – Outcome. *Five-point Likert scale items.*			

	Repurchase Intentions		1 (Strongly Disagree) to 5 (Strongly Agree). Mean: A number out of 5 (=(4 x 5) / 4)
RPI_1	*When I shop for fashion products online, I consider this app first. Adapted*	(Graciola *et al.*, 2018). Also adapted by Antwi (2021).	
RPI_2	*I do most of my online fashion shopping using this app. Adapted*		
RPI_3	*If I could shop online today, I would shop from this app again. Adapted*		
RPI_4	*I plan to do most of my future shopping from this app. Adapted*		
RPI	*Total score for Repurchase Intentions*		
Instruction Manipulation Check. *Five-point Likert scale item.*			
IMC	*Please select the 'Neutral' option for this statement. This is just to screen out random clicking.* *(Adapted. Camouflaged with the NoA statements).*	(Oppenheimer, Meyvis and Davidenko, 2009)	1 (Strongly Disagree) to 5 (Strongly Agree).

3.3.4. Piloting

A pilot study was conducted to ensure the instrument functions well, since self-completion questionnaires do not offer any opportunity to clarify questions from the researcher (Bryman and Bell, 2011). The survey was piloted with ten respondents consisting of four MA students, three working class participants previously residing in the UAE, and three current residents of the U.A.E. Since some of the pilot respondents were based in the EU or UK, two additional multibrand apps – ASOS and ZALANDO were included for respondents unfamiliar with local fashion apps from the U.A.E. In addition to this, the survey was also formally reviewed by two PhDs. Pilot respondents were asked to input their feedback at the end of questionnaire. Based on feedback received, the questionnaire was amended to reflect changes discussed in Appendix 3 – A 3.2.

3.4. Data Collection and Analysis

3.4.1. Data Collection and Target Population

The questionnaire was administered online on various social media platforms – LinkedIn, Instagram, WhatsApp, and Facebook, from August 11th to August 29th, 2021, using a call-for-research (Appendix 3 – A 3.2.). The target population for this study was *U.A.E-based males and females from the Gen Z (ages 18-24) and Younger Millennial (ages 25-29, 30-34) cohort who have purchased more than once from a local pureplay multi-brand fashion app in the past two years*, as these form the core fashion consumers highly likely to have engaged with mobile shopping (Euromonitor, 2020).

3.4.2. Sample Size

196 responses were recorded during the data collection period, out of which 56 were incomplete or did not meet the sampling criteria, and 12 failed the IMC. After discarding these, 128 valid responses were used for the final analysis. Although previous studies have used relatively larger sample sizes ranging from N=242 to N=893 (Hsu and Chen, 2018; De Canio, Fuentes-Blasco and Martinelli, 2021) to minimize sampling error, N=128 was well above the minimum sample size required for the PLS SEM analysis conducted in this research. In addition, according to Central Limit Theorem, since N>=30, the sample size was also suitable to achieve normal distribution required for supplementary analysis using SPSS (Clow and James, 2014).

According to Hair *et al.* (2014) there are two primary ways of determining the sample size for a PLS-SEM based study:

i. **The ten-times rule:** As a rule of thumb, the sample size should be equal to the larger of ten-times the greatest number of formative indicators used to measure a latent variable, or ten-times the maximum number of arrows pointing at a particular latent variable (Barclay, Higgins and Thompson, 1995). In the proposed conceptual model, the largest number of arrows directed at a latent variable are three (i.e., one arrow each from pleasure, arousal, and dominance pointing at repurchase intentions. See Figure 1.). Therefore, the minimum sample size required equals, $\mathbf{N_{min} = 10 \times 3 = 30}$.

ii. **Statistical power and minimum $\mathbf{R^2}$ method:** Assuming the common statistical power of 80%, Appendix 3 – A 3.3. can be used to determine the minimum sample size based on three factors – the greatest number of arrows pointing at an endogenous variable, minimum R^2 values in the endogenous construct, and the desired level of significance (Cohen, 1992). In the proposed model, the maximum number of arrows pointing at an endogenous variable is three (i.e., the three arrows from PAD pointing at repurchase intentions. See Figure 1.) and the desired level of significance is 5%. Therefore, as highlighted in the third row of Appendix 3 – A 3.3., the largest minimum sample size required for this study would be N_{min}= 124, assuming the least value of R^2.

The sample size for this study was **N=128, which is greater than $\mathbf{N_{min}}$= 30, and $\mathbf{N_{min}}$= 124**, and is hence, justified.

3.4.3. Sampling Technique

The respondents were sampled using non-probabilistic sampling, since it would be challenging to acquire a sampling frame using probabilistic sampling for the target population (Bryman and Bell, 2011). This approach was also adopted by other researchers, bearing in mind the challenges of a cross sectional study in terms of economy and time (Hsu and Chen, 2018; Antwi, 2021; De Canio, Fuentes-Blasco and Martinelli, 2021). While some studies used online consumer panels to achieve a more representative sample (Kim *et al.*, 2016; Hsieh, Lee and Tseng, 2021), others such as those of Ali and Bhasin (2019), and Parker and Wang (2016) were based on student and teacher sampling. Despite an adequate number of responses, the student sampling observed in these studies may have led to questionable reliability (Bryman and Bell, 2011; Ali and Bhasin, 2019). Therefore, to elicit responses from multiple demographics, this survey was launched on various online platforms which cater to different consumer groups, for example LinkedIn for working professionals, Instagram for creatives and students, etc. This approach was therefore a combination of convenience, snowball, and self-selection sampling used by several other researchers (Hsu and Chen, 2018; Antwi, 2021; De Canio, Fuentes-Blasco and Martinelli, 2021). Although the study commenced with quota sampling to increase reliability, the strategy had to be modified due to attrition and low response rates (see Appendix 3 – A 3.4. for the originally proposed quota).

3.4.4. Overview of Data Analysis

The data was analyzed used Smart PLS V 3.3.9 and SPSS V 27. Descriptive statistics and preliminary analysis were conducted using SPSS and MS Excel for graphs. Hypothesis testing was performed using Structural Equation Modeling (SEM) on Smart PLS. SEM was conducted in two stages- assessment of the measurement model followed by assessment of the structural model (Hair *et al.*, 2014; Hsu and Chen, 2018; De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021).

Since non-probabilistic sampling is unsuitable for statistical tests, inference was based on the assumption that the sample is chosen randomly from an infinitely large population and follows normal distribution (Clow and James, 2014; Pallant, 2016). Though most of the data collected was ordinal, the use of any parametric tests on non-parametric data has been justified in extant literature (Jamieson, 2004).

Supplementary analysis was concluded on SPSS to study effects of demographics on consumers' repurchase intentions using T-test and ANOVA, observe any significant association between demographics and app usage behaviour using Chi Square tests, and account for non-response bias with independent sample T-tests .

3.5. Reliability and Validity

The reporting of SEM analysis requires the examination of a measurement model consisting of reliability and validity of constructs (Hair *et al.*, 2014). Therefore, the reliability and validity for this study has been discussed in more detail in the section on measurement modeling (Chapter 4).

Reliability was assessed using Cronbach's α and Composite Reliability (CR) (Hair *et al.*, 2014). Convergent validity was tested using the Average Variance Extracted (AVE). Discriminant validity was examined using the Fornell-Larcker criterion and HTMT ratios, and is discussed in Chapter 4 (Fornell and Larcker, 1981; Hair *et al.*, 2014).

Table 7. indicates the values of factor loadings of all reflective indicators (>0.7), CR (>0.7), Cronbach's α (>0.7), and convergent validity using AVE (>0.5) (Hair *et al.*, 2014; Hsu and Chen, 2018; McLean *et al.*, 2019; De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021).

According to Hair *et al.* (2014), items slightly below the threshold loading maybe retained provided they contribute to the construct's validity and do not have loadings less than 0.4. Based on this, PER_1 was deleted despite having a factor loading > 0.7, since it compromised the AVE value for Personalization. PER_4 on the other hand, was retained despite having a factor loading < 0.7 since it contributed to an adequate composite reliability (>0.8) and AVE value (>0.5). Similarly, NoA_1 was also retained despite having a factor loading slightly less than 0.7 since it contributed to appropriate CR and AVE scores. All measures were retained with a minimum of three items as prescribed Hair *et al.* (2010).

Table 7: Reliability and Convergent Validity reported using Composite Reliability (CR), Cronbach's α, and Average Variance Extracted (AVE). See chapter 4 for detailed analysis of the measurement model.

Factor	Loadings
Newness of Assortment	**CR= 0.808**, Cronbach's α= 0.640, AVE= 0.588
NoA_1	0.637
NoA_2	0.839
NoA_3	0.808
Personalization	**CR= 0.813**, Cronbach's α= 0.665, AVE= 0.597 *(Excluding PER_1)*
PER_1 *(Deleted since AVE< 0.5)*	0.730
PER_2	0.872
PER_3	0.817
PER_4 *(Not deleted since AVE > 0.5 on retaining)*	0.604
Transparent User Experience	**CR= 0.902**, Cronbach's α= 0.857, AVE= 0.698
TUX_1	0.807
TUX_2	0.872
TUX_3	0.862
TUX_4	0.798
Ubiquity	**CR= 0.900**, Cronbach's α= 0.834, AVE= 0.749
UBQ_1	0.845
UBQ_2	0.866
UBQ_3	0.885
After Sales Service	**CR= 0.936**, Cronbach's α= 0.900, AVE= 0.831
AFS_1	0.917
AFS_2	0.929
AFS_3	0.888
Arousal	**CR= 0.848**, Cronbach's α= 0.733, AVE= 0.652
ARO_1	0.741
ARO_2	0.797
ARO_3	0.878
Dominance	**CR= 0.809**, Cronbach's α= 0.648, AVE= 0.586
DOM_1	0.743
DOM_2	0.761
DOM_3	0.792
Pleasure	**CR= 0.869**, Cronbach's α= 0.774, AVE= 0.688
PLE_1	0.781
PLE_2	0.852
PLE_3	0.854
Repurchase Intentions	**CR=0.917**, Cronbach's α= 0.879, AVE= 0.733
RPI_1	0.830
RPI_2	0.858
RPI_3	0.867
RPI_4	0.870

3.6. Limitations of Research Design

The cross sectional nature of this study may have potentially weakened causality and hence internal validity (Bryman and Bell, 2011). However, while some longitudinal studies such as that of McLean *et al.* (2019) had several merits, they did not account for non-response bias, especially in the second stage of the study, as other cross sectional studies did (Hsu and Chen, 2018). Therefore, this study, though cross sectional in nature, was made more robust by comparing demographic means of early and late respondents to eliminate any potential non-response bias (Clow and James, 2014). The sample size was also increased compared to the amount required for PLS-SEM analysis in order to minimize any sampling error and enhance the external validity of such a regional study (Clow and James, 2014). In addition, the questionnaire developed for this research was piloted to minimize non-sampling errors (such as wording of questions) possibly encountered during instrument design (Clow and James, 2014). Since the study encompasses differences in gender and age groups, the effect of these variables was also considered in supplementary tests reported in section 4.4.

3.7. Ethics

This research was designed in accordance with UAL's code of conduct, considering respect for persons, integrity, and respondents' privacy during data collection (UAL, 2017). The project was supervised with professional standards by the university-appointed faculty, and was devoid any forms of 'plagiarism, deception, fabrication, or falsification' in its findings (UAL, 2017). This research was not funded externally. Any expenses incurred were borne by the author. The minimum age required to participate in this study was 18 years. Respondents were asked for their consent before participating and were offered a lucky draw incentive in exchange for their time. The winning respondent was notified about their gift voucher without any public disclosure of their identity. All records were stored safely on password-protected systems. The study was also designed to present zero to minimal risks in terms of health and safety and was devoid of any conflicts of interest whether 'real, potential, personal, or professional' (UAL, 2017).